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METHOD FOR STABILIZING TECHNICAL PROCESSES

The invention relates to a method for stabilizing technical processes or technical systems, and is suitable for stabilizing a processing and manufacturing plant.

Specifying tolerance ranges for the quality variables of a process in which a production process is intended to produce a desired product is generally known.

Also known is to model and predict important quality variables of a process using mathematical, statistical or neuronal algorithms, to thereby simulate the effects of changes in manipulated variables on the production process in advance, and only actually adjusting the process given desired results for the quality variables.

Additionally known is to use special mathematical optimization methods to calculate the optimal values for the most important influencing variables for a prescribed quality objective value, see. E. Schnöburg et al., Genetic Algorithms and Evolution Strategies, Addison-Wesley, Germany, 1994, pp. 286-291 and p. 366-378, and US 6.314.413 B1.

Still, instances are very often encountered in technical processes where the prescribed numerical quality value for the target variable can only be achieved with a very high outlay, or even not at all in a stable manner, since the production process and along with it the influencing variables are always subject to certain fluctuations or disturbances. Therefore, there are very many production processes in which the product to be fabricated cannot be manufactured with the prescribed quality at a sufficient stability.

The object of the invention is to indicate a method for stabilizing technical processes that can prescribe the numerical target value at which a product is manufactured with maximum stability (or flexibility) with respect to the quality features of said technical product within the set tolerance limits, and for which all values to be adjusted for the respective manipulated variables can be prescribed as well.

This object is achieved by a method specified in claim 1 for optimizing production in which a global scaling continued fraction analysis is used to calculate the super-flexible and super-stable values for quality and influencing variables, and set them for the production process.

Advantageous embodiments are described in other claims.

Global scaling (GS) is an introduced physical term explaining that the relationships between physical variables like mass, temperature, weight are variable-invariant in real systems, and regularly repeat themselves logarithmically, see H. Müller, Global Scaling, Special 1, Ehlers Verlag 2001, p. 161/162.

This variable-invariant correlation was first illustrated in biological processes by Cislenko, who plotted a logarithmic line charting how the variety of flora and fauna types were distributed as a function of their size and weight, see L. Cislenko, The Structure of Fauna and Flora in Conjunction with the Physical Size of the Organisms, Moscow, 1981, pp. 89-98. It was here demonstrated that the biological systems are not distributed randomly on the logarithmic variable axis, but rather that they always reached their maximum or minimum at identical periodical intervals on the logarithmic line. In technical systems, this correlation is reflected in the fact that all process values possible in the process can never be incorporated into a technical process with equal probability.

Visible in addition to the process-dependent primary structure of a recorded histogram when viewing the histogram for any technical measured variable of an interval z_u to z_o unsmoothed, e.g., a Gaussian distribution, Poissonian distribution or equipartition, is that certain measured values arise more frequently in the fine structure of this histogram, and others less frequently. These irregularities were filtered out in previously existing processes, since they are interpreted as random disturbances. In GS theory, these varying fluctuations in a measured value are regarded as significant, since they can be reproduced.

Therefore, GS makes it possible in particular to calculate those physical values preferably incorporated by technical processes, since GS stipulates

that the values preferred by a technical or natural process can be determined via continued fraction breakdown according to Leonard Euler, Über Kettenbrüche (Continued Fractions), 1737, Leonard Euler, Über Schwingungen einer Saite (String Oscillations), 1748, L. Euler, Leonard Euler and Christian Goldbach: Correspondence 1729-1764 (eds.: A.P. Juskevic, E. Winter), Abh. Deutsche Akad. Wiss. Berlin, Akademie-Verlag 1965, since it is known from Euler that any real number x can be represented by its continued fraction based on equitation (1):

$$x = n_0 + z / (n_1 + z/(n_2 + z/(n_3 + z/(n_4 + z / (n_5 + ..)))) \qquad (1)$$

Variable z here represents the so-called partial counter, the value of which is set to the value 2 for technical optimizations according to GS.

Since the scale invariance arises on logarithmic scales, see Cislenko, all analyses in the GS process are performed from variables logarithmized to base e. This yields equation (2)

$$\ln x = n_0 + 2 / (n_1 + 2/(n_2 + 2/(n_3 + 2/(n_4 + 2 / (n_5 + ..)))) \qquad (2)$$

The respective numerical values depend on the underlying measuring units, so that so-called standard measures y are introduced in GS for all units in use, to which the variables to be evaluated must be correlated. This yields equation (3) as a special basic equation for GS, see H. Müller, Global Scaling, Special 1, Ehlers Verlag 2001, p. 157.

$$\ln (x/y) = n_0 + 2 / (n_1 + 2/(n_2 + 2/(n_3 + 2/(n_4 + 2 / (n_5 + ..)))) \qquad (3)$$

In GS applications, this basic equation (3) is expanded by an angle ϕ, with $\phi = 0$ or $\phi = 3/2$, by which the logarithmic correlation in (x/y) can be shifted prior to a continued fraction breakdown.

This yields the general basic equation (4) for global scaling, according to which any technical measured variable x desired can be broken down:

$$\ln (x/y) - \phi = n_0 + 2 / (n_1 + 2/(n_2 + 2/(n_3 + 2/(n_4 + 2 / (n_5 + ..)))) \qquad (4)$$

wherein x is the technical measured variable measured in its respective unit, y is the natural standard measure for this variable, and $\phi = 0$ or $\phi = 3/2$.

Due to the convergence condition for continued fractions, the coefficients [no, n1, n2, ...] must always be greater in terms of absolute value than the counter, see O. Perron, Die Lehre von den Kettenbrüche (Continued Fraction Theory), Teubner Verlag Leipzig, 1950, p. 62, and are always whole numbers divisible by 3.

These coefficients determine the characteristic properties of measured variable x, and thus represent a so-called continued fraction code. Measured variables that yield only a value for [n_0] when subjected to continued fraction breakdown are situated in a primary node (node of plane n_0), measured values with values of [n_0, n_1] in a sub-node of the plane n_1, and so on. The core region of a node n_i is the area in immediate proximity to a node, i.e., sub-node n_j lies in the –9 to 9 range, wherein j=i+1. According to the GS theory, the following physical properties are now known as a function of the continued fraction code [n_0, n_1, n_2, n_3, ...]:

Continued fraction code example	Property	Comments
[n_0 +3 –3 +3 –3...]	Super flexibility	Measured variable is at edge of a node region, maximally removed from highly fluctuating core region, in a so-called super-flexible region. The underlying system responds flexibly to changes and disturbances.
[n_0 54...] [n_0 57...] [n_0 60...]	Super stability	Measured variable is on a node, and therefore extremely stable. But can only be reached given exact precision, otherwise measured variable is in highly fluctuating core region of node.

[n_0, n_1...4]... [n_0, n_1...5] [n_0, n_1...7]... [n_0, n_1...8]	Relative rest	Measured variable is between two sub-node regions. Measured variable is hence in a region of relatively low fluctuation.

Therefore, the GS analysis makes it possible to determine, for any technical measured variable, whether this variable is stable, subject to large fluctuations, reacts flexibly to disturbances, or lies in a relatively low-fluctuation range. All other combinations arise from these considerations.

The object of the method according to the invention is to determine not just the optimal values for the product, e.g., the torque of a machine part, the optimal gloss characteristics of paint, or the optimal grip of a tire, but at the same time those values for the influencing variables that end up yielding the respective product value, and simultaneously give rise to a particularly robust, stable or flexible production process.

The object is achieved according to the invention with the following procedural steps:

1. Determination of the existing quality variables and their permissible tolerances (input of target variable tolerances)
2. Global scaling analysis within the prescribed tolerances for each quality variable to determine all GS optimal values for this quality variable
3. Recording of process data
4. Process modeling and sensitivity analysis of existing influences for determining the local process influences that yield production with this quality level, and hence for determining the most important influencing variables
5. Process optimization for the or all prescribed GS-optimal target variables by calculating back to the values for the most important influencing variables
6. Execution of a global scaling analysis on the most important influencing variables for the selection of the GS-optimal target

variable, if there are several equally qualified GS-values for the product in the prescribed interval in terms of the product

7. Determination of the optimal process conditions and back-calculation of accompanying influencing variables, in particular the manipulated variables (selection of GS-optimal target variable)
8. Output of manipulating variables to the process and, if necessary, returning back to step 3 (and back calculating)

Each individual procedural step will be detailed below on the example of manufacturing hinges for an automobile supplier based on the drawing:

The drawing shows:

Fig. 1 Measured torque MD of a produced hinge over time (time axis in 10 second increment)

Fig. 2 Histogram of the torque MD with the measuring range 0 Nm to 2.5 Nm on the X-axis

Fig. 3 Histogram of the torque MD with the measuring range 1.0 Nm to 1.5 Nm on the X-axis

Fig. 4 Fine structure of histograms for two production lines for right and left hinges produced 3 days simultaneous in time

a) Hinges left MDL b) Hinges right MDR

Fig. 5 GSC3000 tool for GS analysis of physical and technical variables

Fig. 6 GS analysis of torque (in Ncm) of automotive hinges

Fig. 7 Histogram of generated torques in a range of 0.87 to 0.92 Nm

Fig. 8 Sensitivity analysis of a hinge product (sensitivity of inputs to output variables MD)

Fig. 9 Process optimization via self-organizing maps by automatically back calculating the target variable MD to the input values to be set

Fig. 10 Depiction of possible input variables for hinges with target torque MD = 1.392 Nm

Fig. 11 Histogram of temperature TW for a production line for manufacturing hinges

1. Recording of quality variables and permissible tolerances

Aside from its geometric dimensions, the significant quality variable for a hinge is the so-called torque or swiveling moment MD. Using the hinge in the application described here requires that the torque be produced within a narrow tolerance range, in this example 0.50-2 Nm. The application does not explicitly state which values it should assume within the tolerance range. In this assembly process, the torque MD was measured for each individual hinge in a 100% quality control after assembly, and shown over a period of several days on Fig. 1:

Fig. 2 and 3 depict the histogram for the recorded torque MD with an interval increment of 1 Ncm, first for the entire measuring range of 0-2.50 Nm, and second for the partial range 1.0-1.50 Nm.

The fine structure of the histograms in both illustrations demonstrates the varying scope of the realized torque values in a real process. For example, the value 1.26 Nm (126 Ncm) is realized 70 times in the period shown, while 1.27 Nm (127 Ncm) is realized only 30 times. The following table provides an overview of the extreme values for this frequency distribution:

Measured frequency	Extreme value type	Midpoints of intervals for measured torque values, Ncm
> 64	Accumulation intervals	101, 113, 126, 130, 134
< 42	Gap intervals	100, 104, 106, 112,

		127

This fine structure is not an accident, since it can always be reproduced in a similar structure in every other time period, and is even similar to Fig. 4 for hinges manufactured in the same period of time.

As evident, a fine structure exists for the histograms in both production lines, and they have a certain similarity. An examination of the production lines over several months reveals that each production line and every day has torques that are produced especially frequently, and torques that are produces especially rarely. Since the GS theory precisely predicts such a distribution and histogram structure for physical and technical measured variables, and the production lines for hinges hence act in conformity with GS, a GS optimization is performed to build up a GS-optimal production line.

Presented by example below is the GS analysis of torque for calculating the stable or flexible torque values.

2. Global Scaling Analysis of Target Variable Torque

2.1. Continued Fraction Breakdown of Torque

A torque MD is given in a tolerance range of between 50 Ncm and 200 Ncm. The GS-optimal value within the tolerance range is being sought. The standard measure y for torque is 1.503277E-10 Nm = proton mass * c^2, see Standard Measure paragraph in H. Müller, Global Scaling, Special 1, Ehlers Verlag 2001, p. 129.

A continued fraction breakdown takes place and coefficients n0, n1, n2, etc., are calculated according to equation (4) with $\phi = 3/2$. The value range 50 Ncm – 200 Ncm corresponds to the node region [24±1], or 50 Ncm = [24; -3] and 200 Ncm = [24; +3].

The torque values were calculated via continued fractions according to equation (4) using the GSC3000 from the Institute for Space-Energy

Research in München (IREF), and is shown as an example for a torque value MD = 1.27 Nm on Fig. 5.

The linear average for the tolerance range of 0.5 Nm to 200 Nm and prescribed target variable for an MD controller is 125 Ncm = [24; +6, -3, +3, ...], which explains the dominance of the value 125 Ncm. The value 127 Ncm is equal to [24; +6, -5] per GS. The fluctuations are minimally pronounced in the boundary regions [24; -3] or [24; +3] or in the sub-gaps, e.g., between [24; +5]=133 Ncm and [24; +4]=146 Ncm. Maximum fluctuations are to be expected within the core region of [24; -10]=73 Ncm to [24; +10]=109 Ncm.

The graphic depiction on Fig. 6 showing the torque values as a function of n_0 and n_1 and the phase ϕ illustrates the correlations for values $\phi = 0$ or $\phi = 3/2$, $n_0=24$ and $n_1=-3$ to $-\infty$ or $n_1=+3$ to $+\infty$. The torque values of 33 Ncm to 1082 calculated via the continued fraction according to equation (4) are here recorded over the longitudinal axis of Fig. 6.

If the hinge manufacturing process were neither regulated nor controlled, the frequency of technically generated torque values would be distributed according to Fig. 6. The white areas on Fig. 6 depict torque values that arise relatively infrequently (so-called gap regions), while the gray areas depict regions with frequent torques, and the dark gray areas represent so-called node regions of the torque.

However, since the target $MD_{setpoint}$=125 Ncm was prescribed in this production instance to the production controller, the distribution of the technically realized torques deviates from this theoretical distribution, and is as shown on Fig. 2.

Values in the node regions, here around 89 Ncm, 124 Ncm and 173 Ncm, can technically not be stably produced according to GS, since fluctuations and disturbances always arise in proximity to the node, see table, p. 5 and example on Fig. 7.

Fig. 7 shows that the range 0.88 Nm to 0.92 Nm is associated with large fluctuations in the actually produced hinge torques, meaning that the value 0.89 Nm cannot be stably produced in practice.

Global calling optimization of hinge production essentially involves two parts:

The first goal is to maintain the production quality to be achieved. If possible the torque MD of each hinge is to be generated in the middle of the tolerance interval at minimal tolerance fluctuations ΔMD. For this reason, rated variable ranges with minimal fluctuations are optimal, i.e., values of between

$$MD_{sub1} = 133 \text{ Ncm} = [24; +5] \text{ and } MD_{sub2} = 146 \text{ Ncm} = [24; +4].$$

Hence, the optimal rated value for hinge production in a tolerance range of 50 to 200 Ncm lies in the logarithmic mean of 133 Ncm and 146 Ncm, i.e., at 139.2 Ncm.

The second goal in hinge production is to make the hinge manufacturing process as robust (or flexible) relative to disturbances as possible. The torque MD essentially arises in the production process as the result of so-called oversize. The oversize is the bolt diameter of the hinge plus twice the bushing wall thickness, and is greater than the hinge hole diameter into which the bolt is pressed.

In this exemplary application, the individual parts of the hinge are subject to tolerances that cannot be further reduced for reasons of cost owing to the mechanical production, so that the rated variables must also be optimally determined according to GS even for individual parts inside each tolerance range. The hinge bolt and hinge hole diameter lie at around 12 mm, while the bushing wall thickness measures around 0.48 mm. Various empirical modeling methods are known for modeling the dependency of torque MD on individual parts.

In this application, an empirical data mining method for modeling is described, since the maximum possible precision for the functional

correlation between torque and influencing variables is here the key. Any other modeling process, e.g., linear modeling between oversize and torque, acts accordingly, but has less modeling accuracy.

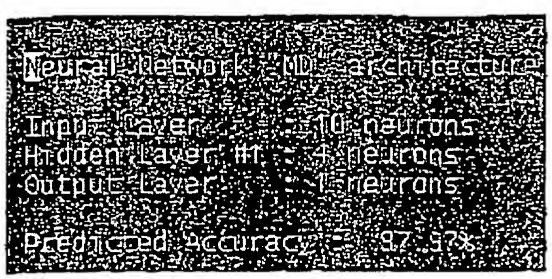
3. Recording of Process Data

Various measuring transducers and control/instrumentation technology are used in prior art to write and archive the process data in a prescribed process increment, 10 seconds in the exemplary application.

4. Process Modeling and Sensitivity Analysis for the Target Variable

Various methods, analytical (e.g., differential equations) or empirical (e.g., linear and non-linear regressions or neuronal networks) are used in prior art, depending on how good the process can be analytically described. In manufacturing processes, e.g., involving complex assembly, knowledge-based process methods are also used, in which the behavior of the process is learned by its process data, see M. Polke, Prozessleittechnik (Process Control Engineering), Oldenbourg verlag, München/Vienna 1994, 813-817.

In the example at hand, process modeling was accomplished via neuronal network modeling. The achieved accuracy measures just under 88%, i.e., the model can be used to estimate the torque value from 10 input variables at just under an 88% accuracy relative to the measuring range of the torque measurement.



It is further known to realize the quantitative dependence of a quality variable, in this example torque MD, on its influencing variables by way of a model-based sensitivity analysis, see R. Otte, Selbstorganisierende

Merkmalskarten zur multivariaten Datenanalyse komplexer technischer Prozesse (Self-Organizing Feature Cards for Multivariate Data Analysis of Complex Technical Processes), Shaker Verlag, Aachen, 1999 and R. Otte et al., Data Mining fuer die industrielle Praxis (Data Mining for Industrial Practice), Carl Hanser Verlag, 2004. Fig. 8 shows the results of a sensitivity analysis based on the aforementioned neuronal model of hinge production.

Fig. 8 shows that the most important influencing variable for torque MD is the bolt DB1, then the bolt DB2, then the calibration mandrel DK. The temperatures TW and TU have the least process influence on the torque. This means that changes in temperature will on average result in relatively smaller changes in torque.

Procedural step 4 automatically identifies those input variables that influence the target variable value, torque MD in the example.

5. Process Optimization for a GS Optimal Target Variable Value

In procedural step 5, the specific quantitative rated values are determined for the most important influencing variables or manipulated variables of procedural step 4, in order to arrive at the prescribed target variable value.

In prior art, empirically learned models are inverted for optimization tasks in order to calculate the accompanying influencing variable values for given target variables. For example, the behavior of the process can be imaged via self-organizing maps, see EP 0 845 720 B1 and R. Otte, Selbstorganisierende Merkmalskarten zur multivariaten Datenanalyse komplexer technischer Prozesse (Self-Organizing Feature Cards for Multivariate Data Analysis of Complex Technical Processes), Shaker Verlag, Aachen, 1999. Fig. 9 presents such a model-based data analysis based upon the self-organizing maps method.

Using a process model for optimization tasks makes it possible to calculate the target variable, MD in the example, for each prescribed, GS-optimal value, the input variables of which end up leading to the target value. Hence, the accompanying values for the influencing variables are

back calculated according to the invention for each GS calculation of the target variable value.

As an example, Fig. 10 shows values for selected input variables calibration mandrel DK, temperatures, TW and TU, hinge half diameter DS, bushing wall thickness BW and bolt diameter DB1, DB2, DB3 for the GS-optimal target variable MD = 139.2 Ncm = 1.392 Nm.

Determined as a result are the input variables the lead to a GS-optimal target variable value y_{GS}, MD = 1.392 Ncm in the example.

6. Global Scaling Analysis of Most Important Influencing Variables

Procedural steps 1 and 2 are used to determine all GS-optimized values y_{GSI} of the target variable in the prescribed tolerance range y_{min} and y_{max}. Procedural steps 3, 4 and 5 are used to ascertain the accompanying input variable values of the process.

If there is only a single optimal GS-value in the interval from a product standpoint, the procedural step 6 described here is skipped, and the manipulated variables belonging to the GS-value y_{GSI} are calculated according to procedural steps 5 and 7. If several equal GS optimal values y_{GSI} are present, then selection via the GS analysis of input variables takes place by using procedural step 5 multiple times, i.e., back calculating the input variables leading to an optimum y_{GSI}.

The numerical values for the input variables are determined in this way. These numerical values are also subject to the GS structure, as shown on Fig. 11 using temperature TW as the example.

After determining the specific input variable values according to procedural step 5, the GS analysis is performed according to procedural step 2 for each of the found input values x_{ni}. The GS-optimal values are determined for the most important input variables in this way. The GS-optimal input values depend on the type of input variable.

The input variables are GS-optimal for the following types:

a) Input measured variables: Optimum per GS by determining the maximum probability of occurrence, since these value realizations will also be encountered most frequently in the future.

b) If the input measured variables are measured values for technical products, the rated variables for these values scan be optimized per GS.

In this case, for example, the bushing wall thickness BW is to be optimized in a range of 0.46 mm to 0.5 mm.
BW_{lower} = 0.46 mm = [21 3 3 –3 3 5]
BW_{rated} = 0.48 mm = [21 3 3 21 6 –9]
BW_{upper} = 0.5 mm = [21 3 6 –3 3 –3]
Therefore, the value BW=0.471 mm is equal to [21 3 3 –5] per GS as the rated value, and hence optimal , since it lies in a gap at n_3.

c) Input manipulated variables: Optimization per GS with regard to super-flexibility, since these values react the least sensitive to changes in the value itself and in the process.

In procedural step 6, a GS-analysis is performed for each GS-optimal target variable value per procedural step 2 and its accompanying input variables per procedural steps 4 and 5, so that the process is subjected to a complete GS-analysis.

7. Determination of the Optimal Process State

In procedural step 7, the GS-optimal process state is selected from the entirety of process states possible per GS, and the accompanying manipulated variables are determined.

The process optimum is reached for the maximum number of GS-optimized input variables for which the target variable y_{GSI} is just GS-optimal. If several target variable values are equal, the value y_{GSI} lying more in the logarithmic mean of the y_{min} and y_{max} interval is the optimal one.

The sub-quantity of manipulated variables $x_{StelliGS}$ is read out from the quantity of input variables x_{1GS}, x_{2GS}, x_{3GSi}, ..., x_{nGS} belonging to the found optimum y_{GS}.

As the result, the optimum for the manufacturing and processing was found, and the manipulated variables $x_{StelliGS}$ for achieving the optimum are output to the process via the existing control/instrumentation technology.

8. Output of GS-Optimal Values to the Process

The GS-optimized values for the manipulated variables of the optimal process state per procedural step 7 are output to the technical or chemical process via control/instrumentation technology or an SPS, for example, so that the process is optimized according to the invention per GS.